11-2016

Wholesale Peak Demand Pricing

Jarek R. Hunger
Portland State University

Wholesale Peak Demand Pricing

by

Jarek R Hunger

An undergraduate honors thesis submitted in partial fulfillment of the

requirements for the degree of

Bachelor of Science

in

University Honors

and

Economics

Thesis Adviser

Peter Stiffler

Portland State University

2016

Wholesale Peak Demand Pricing

A Comparison of Coincidental and Non-Coincidental Peak Based Demand Charges on Wholesale Full-Requirements Customers of Bonneville Power Administration

By Jarek R Hunger

Most public utilities get to set their own power rates, subject to regulation. For many customers, this power rate is priced based on the quantity of energy taken. In addition, pricing based on the time of use is becoming more common. Renewable energy is changing the landscape for power utilities. It is reducing the market price of energy, especially during times of high solar and wind generation. Since utilities still need to recover their costs, new pricing structures are needed. A method of pricing that some utilities use, which is getting more attention now that larger amounts of renewable generation are coming online, is a charge for the peak amount of energy consumed over some time interval.

A utility needs to have a generation and transmission system ready to serve the highest level of load incurred at any time. To give a simplified example, if a customer uses 1 MW most of the time and then peaks at 100 MW for a single hour, the utility must build a system which can serve 100 MW. Under a simple time of use pricing scheme, the cost of having 99 MW on standby most of the time is being divided over many customers, even if their loads are a flat 10 MW all hours. Since the utility must recover its costs this means that the other customers with flatter loads pay a higher rate than they should have to, based on how much cost they are incurring on the system. This also means that customers with flatter loads subsidize customers with peaky loads; weakening the price signal they receive to flatten their loads.

The purpose of a demand charge is two-fold. First, it allocates the higher cost of a peaky load to those customers with peaky loads. Second, it creates the incentive for customers to flatten their loads by encouraging demand response during peak energy use periods. If this second goal is realized it will result in lower total costs on the utility since their system will not need to support as high of a peak. This will cause lower energy rates for all customers (all else equal) since the utility will have a lower total cost to recover through energy rates.

Currently, there are two methods of evaluating demand charges. The first and most popular method is to charge customers based on their electricity load during the utility's peak electricity usage – called coincident peak pricing. This is intuitive because the utility's system peak determines the maximum level of demand they must be ready to serve in terms of generating the peak level of power and having the transmission to serve it. Through this mechanism the utility can directly pass through the price signal related to acquiring additional generating and transmission capacity. The problem with this method is that customers are left guessing when the peak might occur. If a customer is unsure of when the system peak will occur, they are similarly unsure if any actions they take to reduce their load during that time will be worth taking.

This problem has long been in the utility industry. In 2011 Bonneville Power Administration (BPA) enacted demand rates which base demand charges on what is called non-coincident peaks. This method bases the demand charge on the individual customer's peak load, not their load during the system's peak. The downside to this method is that it sends an imperfect price signal to customers whose peak is different than the system peak, since they are being incentivized to reduce their peak during an hour that is not BPA's peak. However, since BPA's peak is an aggregation of customer usage, if all customer peaks go down, BPA's system peak should go down as well. The benefit of non-coincident pricing is primarily that it gives the customer much more agency over their demand charge since it is based on something they can potentially control. This concern for customer agency was the primary motivation for BPA to move to non-coincident peak pricing (Bonneville Power Administration, 2008). As such, the question that this thesis seeks to evaluate is whether this change results in larger system-wide benefits due to customers being more invested in reducing their peak. This will be tested by looking at the results of BPA’s methodology change in 2011.

This thesis is from the perspective of a public utility, as opposed to an investor-owned utility, since it is a study of the Bonneville Power Administration. This means that power rates will be discussed as a mechanism to recover costs and not to generate a profit. Insofar as a “profit” appears to exist, it will simply represent an over collection of monies which will be “returned” to rate payers in the form of lowered power rates in the future.

Literature Review

As of today there has never been an apples-to-apples comparison of non-coincident demand charges to coincident demand charges and their comparative effectiveness. Since demand charges are relatively new for many utilities the discussion has centered around whether they are worth implementing at all, and if so, how (Rocky Moutain Institute, 2016). Demand charges for residential customers is a topic of increasing interest, recently, as the technology has developed to a level where residential demand charges are feasible (Faruqui, The Economics of Dynamic Pricing and Smart Metering, 2006).

While there has been a substantial amount of work done quantifying the load impacts of various demand charges this work has mostly been done outside of traditional peer-reviewed research in the form of company reports or white papers. In addition, most of this research is on power sales at the retail-level as opposed to at the wholesale-level. No work has analyzed utility incentive to reduce peakyness outside of the regulated retail setting.

The impact of both demand charges and time of use rates was first investigated in the 1990’s. One example is Taylor and Schwarz in 1990 which investigated the long run effects of the time of use rate offered by Duke Power (Taylor & Schwarz, 1990). They found that time of use rates had increasing effects over time that made them more effective than originally expected at reducing peak usage.

Subsequently, a few different studies have been conducted which evaluated the effect of various types of demand charges. Wolak in 2007 studied the effect of critical peak pricing (a demand charge) for 123 customers of City of Anaheim Public Utilities and found a load reduction of about 12 percent during declared peak times (Wolak, Residential Customer Response to Real-Time Pricing, 2007). Wolak did another study in 2010 which looked at the effect of demand charges compared to demand rebates and found an aggregate effect of about 12.43 percent (Wolak, An Experimental Comparison of Critical Peak and Hourly Pricing, 2010). Probably the most authoritative study currently was done by Baltimore Gas and Electric Company in 2008 and 2009. They had about 1000 customers who were randomly placed with either critical peak pricing or peak time rebates. Some of these customers were then paired with technology to help them communicate peaks as well as give customers control over usage. They found a peak reduction range of 18 to 33 percent for each of the summers (Faruqui & Sergici, Dynamic pricing of electricity in the mid-Atlantic region, 2011).

All of these studies have been focused on residential use impact – not wholesale customers. The Rocky Mountain Institute points out there is, "comparatively little industry experience with mass-market demand charges relative to time-based rates" (Rocky Moutain Institute, 2016). They also acknowledge that there is little empirical evidence to provide insight on the impact of demand charges beyond cost recovery. This is especially true with regards to wholesale customers.

As such, this study seeks to provide some new evidence on the comparative effects of two different types of demand charges as well as provide some estimates of the overall effect. BPA's demand charge is a good candidate for testing the impact of non-coincident demand charges compared to coincident demand charges because most aspects of their demand charge stayed the same throughout the period. Before and after 2011 the demand charge was ex post (applied based on when the peak ended up being after the fact), based on the peak average hour each month, and collected roughly the same amount of overall revenue (Bonneville Power Administration, 2012). Given the lack of research, this is a prime opportunity for investigation. Principally I want to show how this new rate structure affected customer loads during BPA's system peak.

Methodology

Many of BPAs customers are not subject to the demand charge due to their product choice, are inconsistently effected, or were not customers during the whole time period. In particular, BPA offers a product called "Slice" which allows customers to pay for a percentage of the system's costs and receive a percentage of the system's output. Since the Slice product is not tied to load shape, Slice customers are not subject to a demand charge since they pay for a portion of the system costs, and do not effect BPA's need to expand the system. As such I used the 91 of 116 customers which were customer's during the whole period and have their entire loads provided by BPA (a list of customers is included in appendix 2). These customers represent total load of a little more than 20,000 gigawatt hours per year.

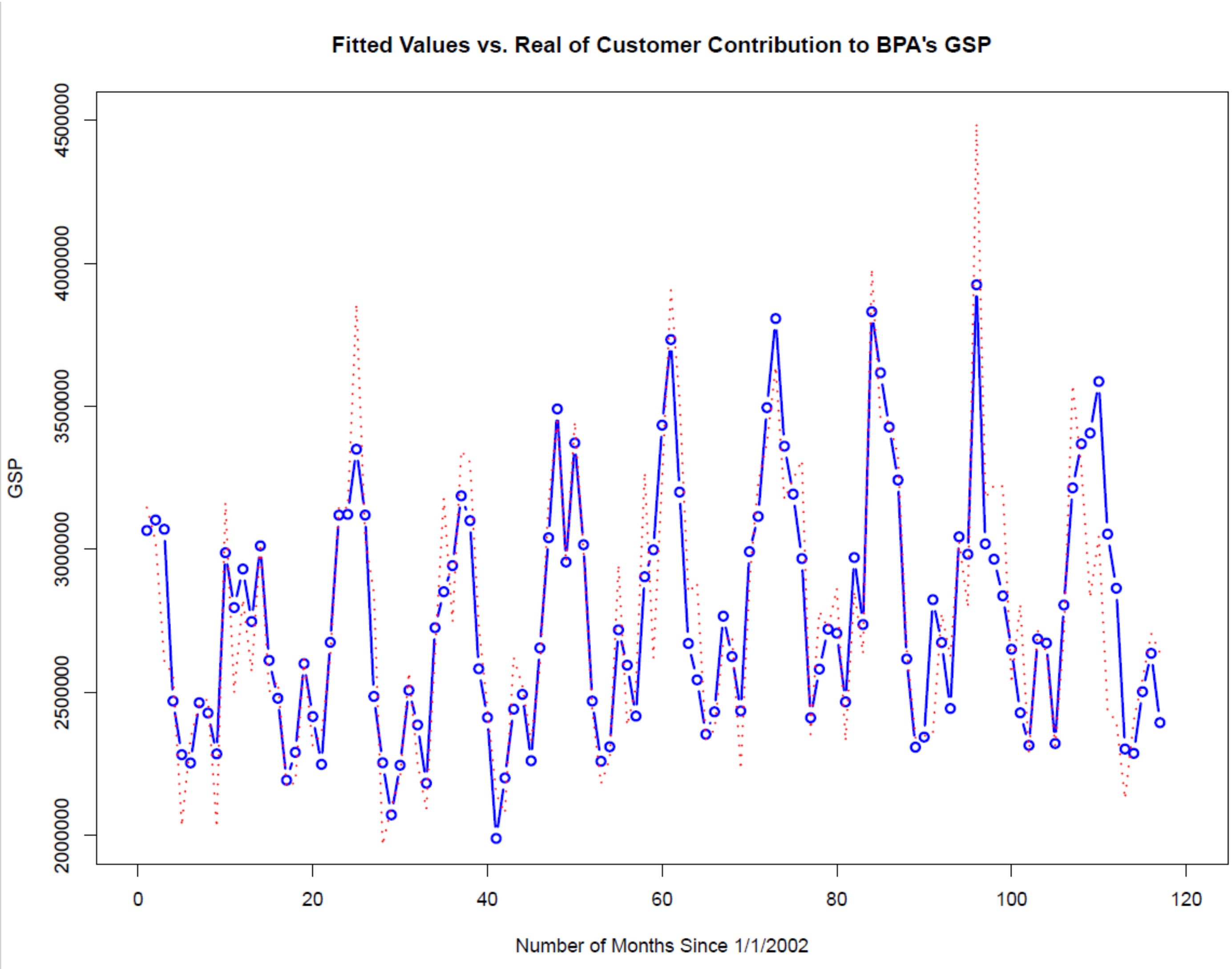
In order to test the impact of the non-coincident demand pricing I created a model of system peaks (GSPs) in Kilowatts (KW) including as regressors: total electricity usage (TRL) in Kilowatt-Hours, the electricity rate for heavy load hours (HLH PF Rate) in Dollars per Megawatt-Hour, the demand rate in Dollars per Killowatt, the extremeness of weather (explained in Appendix 3), and the sum of the population of Oregon and Washington. Additionally, I included dummy variables for the months of the year and a time trend. The model was estimated using data from January 2002 to September 2011, approximately ten years before the change in pricing structure and during which coincident peak demand pricing was still in effect. Here are summary statistics of the data used (both before and after the change) for reference:

			Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
SUMGSP	*The sum of customer loads during BPA's system peak*	*In MW*	1966008	2427478	2699859	2757837	3037307	4489010
SUMTRL	*The sum of customer loads during the month*	*In KWh*	1328912257	1508973771	1609373295	1655830842	1743219547	2243862182
HLHPF Rate	*The "Priority Firm" energy rate during heavy load hours*	*In $/MWh*	12.53	21.03	28.47	26.86	32.59	41.55
Demand Rate	*The demand rate paid as described in this paper*	*In $/KW*	0.75	1.43	2.03	3.53	2.31	11.47
Weather Extremeness	*The weather metric which is described in appendix 3**	*	56.26	90.95	247.22	281.19	462.87	658.81
SUMPop	*The sum of the populations of Oregon, Idaho, and Washington*	*In people*	10906145	11298748	11865299	11787149	12274401	12667196

Graphs of these data sets over the time period are included in appendix 6. Population is a steadily increasing variable and is calculated as the sum of the populations of Oregon, Idaho, and Washington. Weather extremeness is a seasonal variable which is calculated as the average sum of degree-hours outside of 65-75 degrees Fahrenheit, it is described in more detail in appendix 3. The demand rate is a seasonal variable which increased substantially in 2011 when the rate structure was changed. The HLH PF Energy rate is a seasonal variable which increased substantially in 2011 as well when the rate structure was changed. The total retail load variable is also a seasonal variable which tracks the changes in GSP pretty closely.

Results

The fit of the model to the real data is shown below, where the blue line is the fitted values and the red line is the real values. Several assumption testing plots are included in Appendix 4.

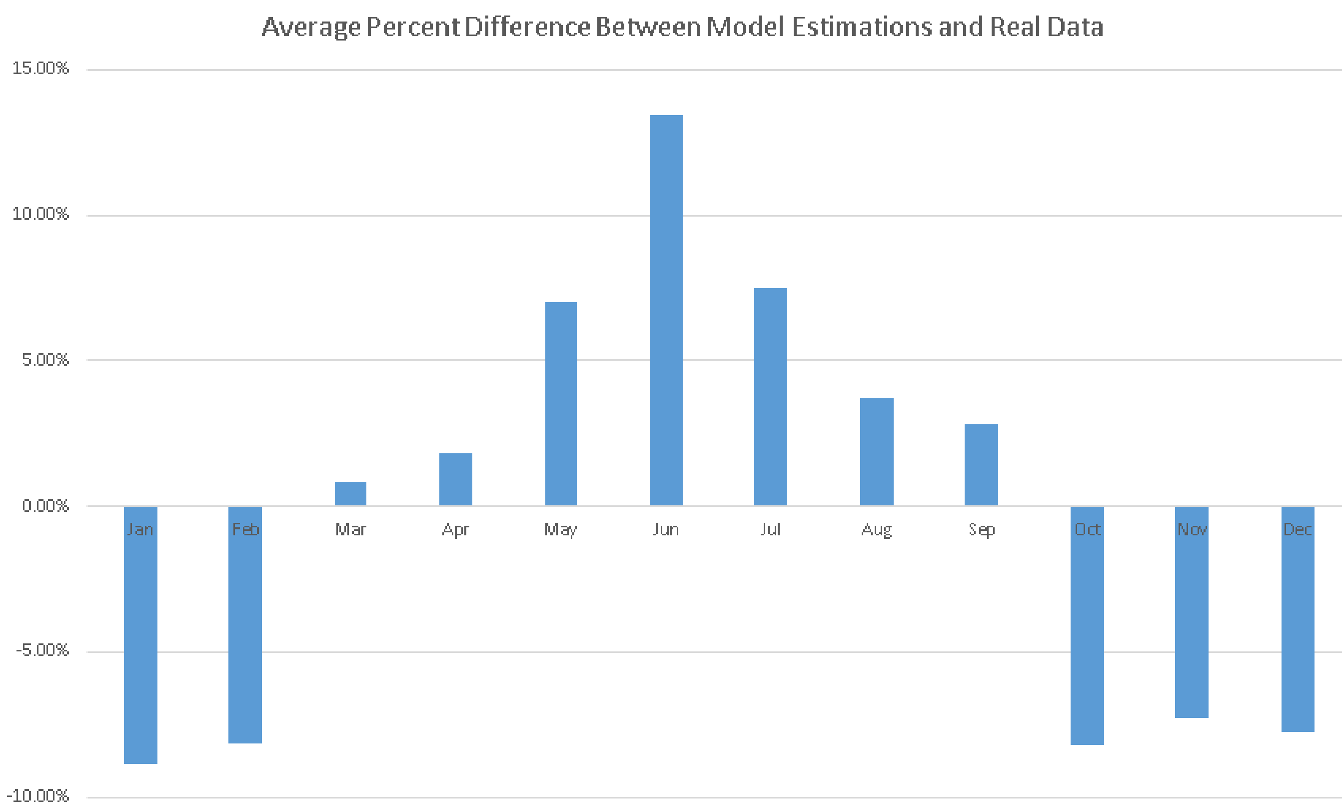


This estimated model was then given input data for October 2011 to September 2014 to generate estimated GSPs for those time periods. Since the model was generated using data from before the rate structure change, the estimated GSPs should represent what they GSP would have been if the rates were never changed. The difference between the model's estimations and the true values are what is being used to account for the effect of the rate structure change. So, if given the new data, the model expected a GSP of 400,000 and then the real data was 350,000 the interpretation would be that the rate change resulted in a 50,000 reduction in GSP that month. The estimated model has an adjusted R-squared of 0.7702 and an F-statistic of 23.87 (full regression statistics can be found in appendix 1). The resulting estimated model is as follows:

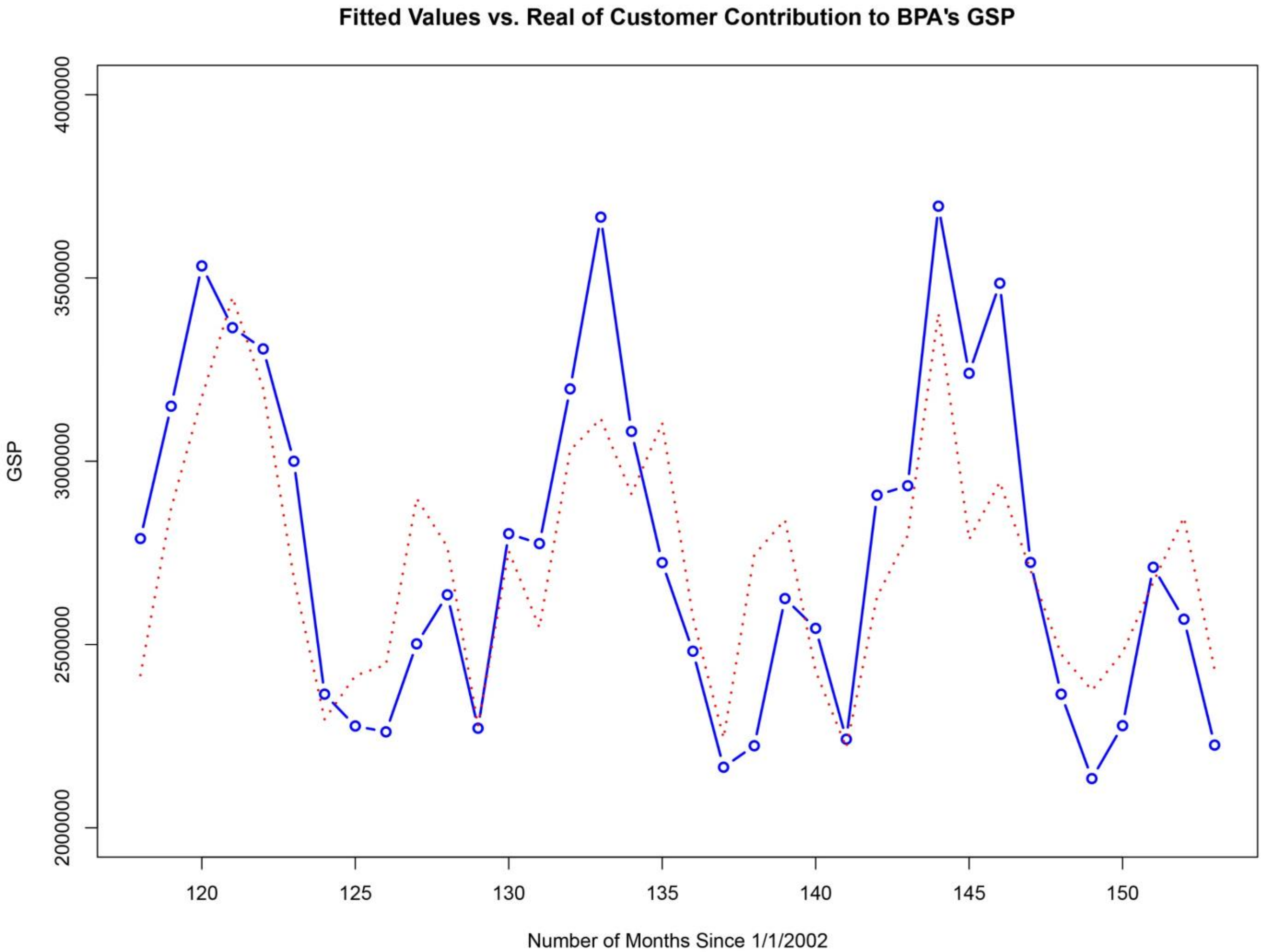
$$GSP = (-13318.6 * TimeTrend) + (0.0015347 * TotalRetailLoad) - (5335.93 * HLHEnergyRate) - (1422.59 * DemandRate) + (1719.26 * Weather) + (0.97555 * Population) - (174728 * Jan) + (252903 * Feb) + (92555 * Mar) + (218786 * Apr) + (138568 * May) + (362998 * Jun) + (442078 * Jul) + (532354 * Aug) + (556824 * Sept) + (717400 * Oct) + (247222 * Nov) - 10864780$$

The coefficients on the months are the fixed effects of each month relative to December which is the base case. The overall time trend was to decreasing GSPs, this is likely due to a mix of the rate change effect as well as conservation. Total retail load follows GSP very closely since most customers have a consistent load factor. The energy and demand rates are set by BPA as monthly rates. Weather varies depending on how hot or cold it was, and for how long, each month. Population increases steadily each year. It is important to note that the demand rate should not be interpreted as customer elasticity since it is not based on customer level responses to price changes but rather aggregate response coincident to BPA's peak.

The model was then used to generate estimated GSP values based on real data for Oct 2011- Sept 2014. On average the monthly GSP was 0.25 percent lower than the model estimated. While the monthly peaks on average dropped by 0.25 percent, the difference each month was substantially different. The following graph shows the average difference between the model estimations and the actual meter data over the three-year period (the full three years can be found in appendix 4).



As shows in the graph above, the rate structure change seems to have caused peaks to increase from March to September and decrease from October to February. Since the winter months are the most expensive for BPA, and when monthly peaks are highest, this should result in net savings. Similarly, the difference between the winter GSPs and summer GSPs was substantially moderated. The difference between the highest winter GSP and lowest summer GSP in the first year (October 2011 – September 2012) was 92 percent of what was expected by the model, in the second year it was 60 percent of what was expected, and in the third year it was 66 percent of what was expected. This means that while the average monthly peak went barely went down, this does not tell the full story. The monthly peaks were substantially moderated. The following is a graph of the model estimations in blue with real data in red.



Conclusions

The change in rate structure did cause an average decrease to peaks. However, individual monthly effects varied widely. Since most of the increased months were in the summer months where demand is lower in general, it is unlikely that this increase will result in a substantial increase to costs for BPA. Alternatively, since the extremeness between valleys and peaks was reduced, it should be easier to plan for going forward. The model expected an average monthly deviation from the annual mean of 13.6

percent; but the actual average deviation was only 9.5 percent. With only three years to look at with the new pricing it is hard to draw strong conclusions about the persistence of winter peak reduction, but based on these results the best expectation is that the highest monthly peaks are lower under non-coincident peak pricing than they were under coincident peak pricing.

Further Research

Having a restricted sample of only three years post rate design change to look at restricts the ability to draw sweeping conclusions. This research should be followed up in a few years to see if the effects documented here persist.

One substantial effect that was not accounted for in this research was conservation. Data on conservation is difficult to standardize but doing so would allow for better isolation of effects. It is likely that some of the winter peak savings shown in this study are due to better conservation in the last few years that primarily impacts winter.

Appendix 1

```
Coefficients:
                          Estimate          Std. Error t value Pr(>|t|)
(Intercept)          -10864780.1018897  8612524.1027110  -1.262 0.210090
TimeTrend               -13318.6061292    10520.7205488  -1.266 0.208505
SUMTRL                       0.0015347        0.0005953   2.578 0.011411
HLHPFRate                -5335.9301565     6945.5447424  -0.768 0.444166
DemandRate               -1422.5954595    64730.6875026  -0.022 0.982510
WeatherExtremeness        1719.2649992      882.3043241   1.949 0.054173
SUMPop                       0.9755491        0.8006735   1.218 0.225964
Jan                    -174728.6305900   163052.1098557  -1.072 0.286500
Feb                     252903.3861370   199153.7531001   1.270 0.207101
Mar                      92555.2212689   185136.5548847   0.500 0.618234
Apr                     218786.1297464   224507.6644368   0.975 0.332176
May                     138568.4170016   262040.7616537   0.529 0.598124
Jun                     362998.2304142   291764.2782853   1.244 0.216382
Jul                     442078.3481166   308490.3601083   1.433 0.154997
Aug                     532354.8869908   302244.3024229   1.761 0.081268
Sept                    556824.3633276   270103.2443874   2.062 0.041874
Oct                     717400.8627622   210578.4600152   3.407 0.000951
Nov                     247222.5817245   150046.5787253   1.648 0.102597
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 226800 on 99 degrees of freedom
Multiple R-squared:  0.8039,    Adjusted R-squared:  0.7702
F-statistic: 23.87 on 17 and 99 DF,  p-value: < 0.0000000000000022
```

Appendix 2

Customers Included in Study:

Alder Mutual Light Company
Benton Rural Electric Association
Big Bend Electric Cooperative, Inc.
Canby Utility Board
City of Albion
City of Ashland
City of Bandon
City of Blaine
City of Bonners Ferry
City of Burley
City of Cascade Locks
City of Centralia
City of Cheney
City of Chewelah
City of Declo
City of Drain
City of Ellensburg
City of Forest Grove
City of Hermiston

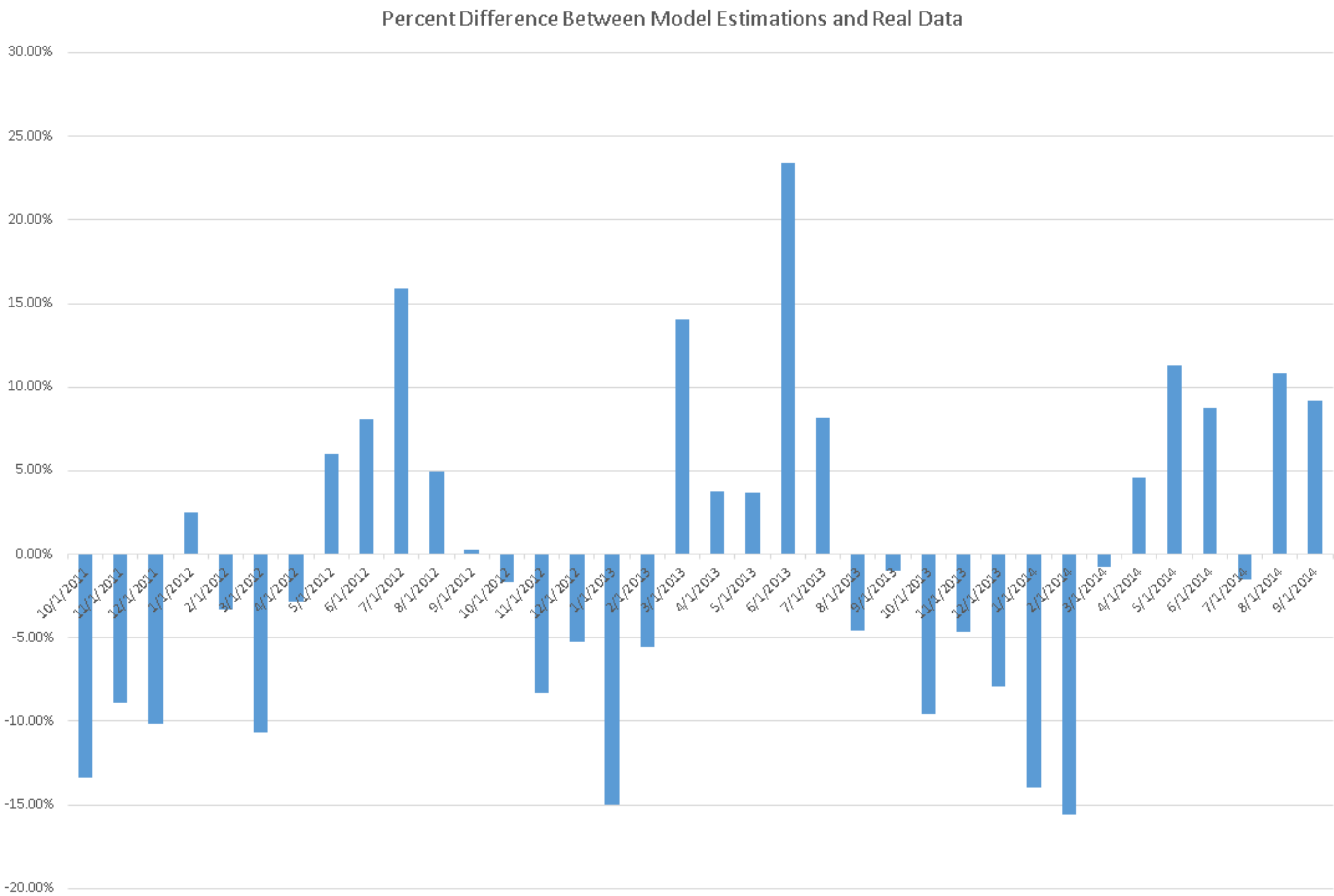
City of Heyburn
City of McCleary
City of Milton
City of Milton-Freewater
City of Minidoka
City of Monmouth
City of Plummer
City of Port Angeles
City of Richland, Washington
City of Rupert
City of Soda Springs
City of Sumas
City of Troy
Columbia Basin Electric Cooperative, Inc.
Columbia Power Cooperative Association
Columbia River People's Utility District
Columbia Rural Electric Association
Consolidated Irrigation District No. 19
East End Mutual Electric Company, LTD
Elmhurst Mutual Power & Light Company
Fairchild Air Force Base
Farmers Electric Company, LTD
Flathead Elec Coop
Glacier Electric Cooperative, Inc.
Harney Electric Cooperative, Inc.
Hood River Electric Cooperative
Idaho County Light & Power Cooperative Association, Inc.
Inland Power & Light Company
Kootenai Electric Cooperative, Inc.
Lakeview Light & Power
Lower Valley Energy, Inc.
McMinnville, City of
Midstate Electric Cooperative, Inc.
Missoula Electric Cooperative, Inc.
Modern Electric Water Company
Nespelem Valley Electric Cooperative, Inc.
Northern Wasco County People's Utility District
Ohop Mutual Light Company
Orcas Power & Light Cooperative
Oregon Trail Electric Consumers Cooperative, Inc.
Parkland Light & Water Company
Peninsula Light Company
Public Utility District #1 of Skamania County
Public Utility District No. 1 of Asotin County
Public Utility District No. 1 of Clallam County
Public Utility District No. 1 of Ferry County
Public Utility District No. 1 of Kittitas County
Public Utility District No. 1 of Mason County
Public Utility District No. 1 of Wahkiakum County

Public Utility District No. 1 of Whatcom County
Public Utility District No. 3 of Mason County
Ravalli County Electric Cooperative, Inc.
Riverside Electric Company, LTD
Salem Electric
South Side Electric, Inc.
Springfield Utility Board
Surprise Valley Electrification Corporation
Tanner Electric Cooperative
Tillamook People's Utility District
Town of Coulee Dam
Town of Eatonville
Town of Steilacoom
U.S. Department of Energy - Richland Operations Office
Umpqua Indian Utility Cooperative
United Electric Co-op, Inc.
US DOE Natl Energy Technology Lab
USN Bangor
USN Everett-Jim Creek
Vera Water & Power
Vigilante Electric Cooperative, Inc.
Wasco Electric Cooperative, Inc.
Wells Rural Elec Coop

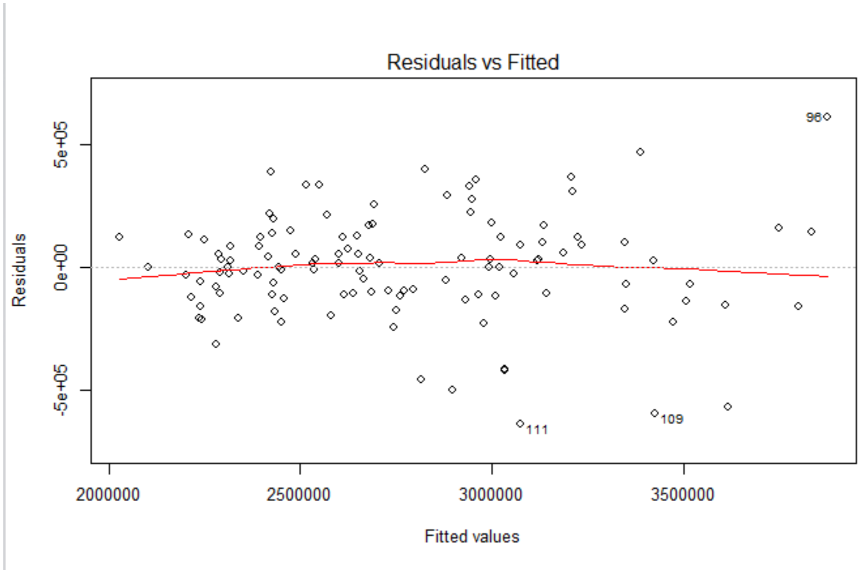
Appendix 3

Extremeness of Weather in a month is a calculated value defined as the average of the Extremeness of Weather each day of the month. Extremeness of Weather for a day is defined as the sum of substantial cooling degree hours and substantial heating degree hours for that day. Substantial heating degree hours are defined as the sum of degree-hours below 65 degrees each hour of the day. Substantial cooling degree hours are defined as the sum of degree-hours above 75 degrees each hour of the day. In other words, it is the average number degree-hours above 75 and below 65 degrees Fahrenheit each day, over the month.

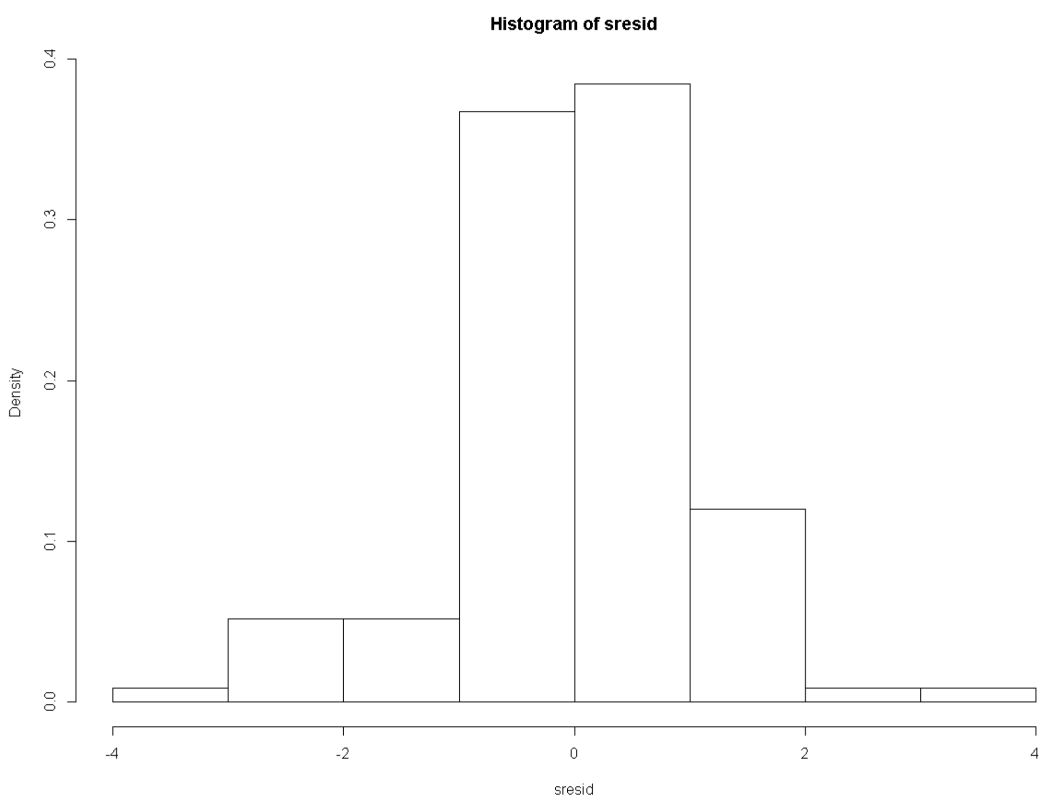
Appendix 4


Percent Difference Between Model Estimations and Real Data
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
-5.00%
-10.00%
-15.00%
-20.00%
10/1/2011
11/1/2011
12/1/2011
1/1/2012
2/1/2012
3/1/2012
4/1/2012
5/1/2012
6/1/2012
7/1/2012
8/1/2012
9/1/2012
10/1/2012
11/1/2012
12/1/2012
1/1/2013
2/1/2013
3/1/2013
4/1/2013
5/1/2013
6/1/2013
7/1/2013
8/1/2013
9/1/2013
10/1/2013
11/1/2013
12/1/2013
1/1/2014
2/1/2014
3/1/2014
4/1/2014
5/1/2014
6/1/2014
7/1/2014
8/1/2014
9/1/2014

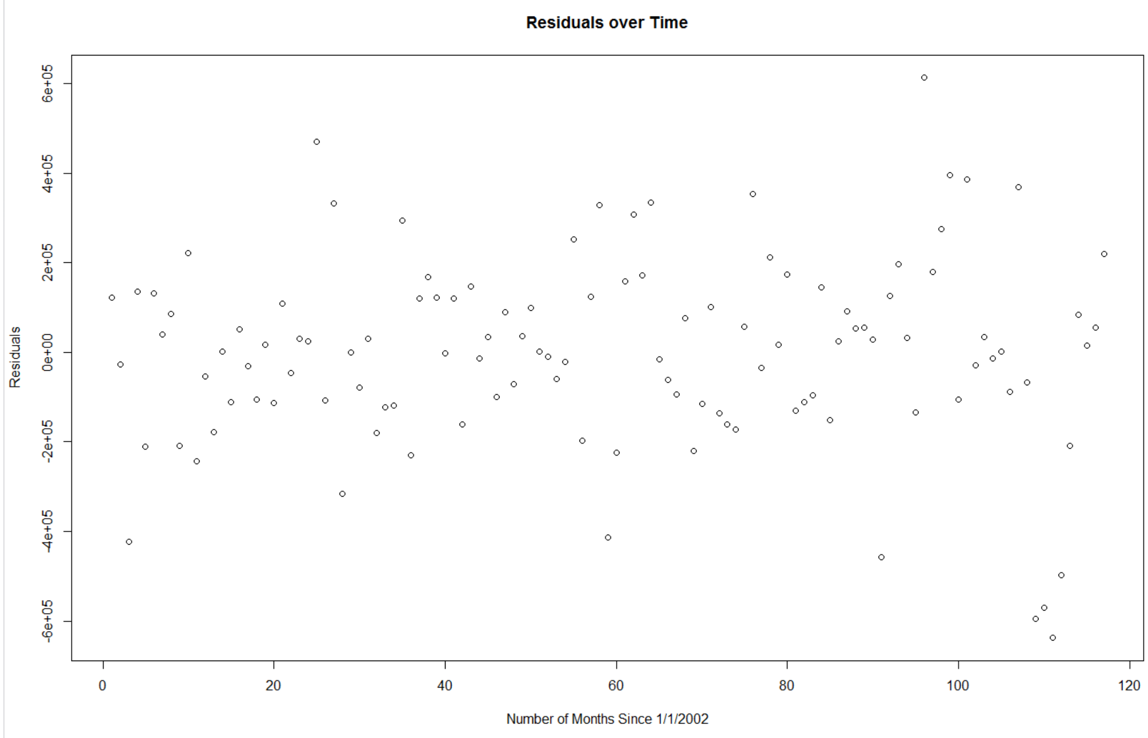
Appendix 5

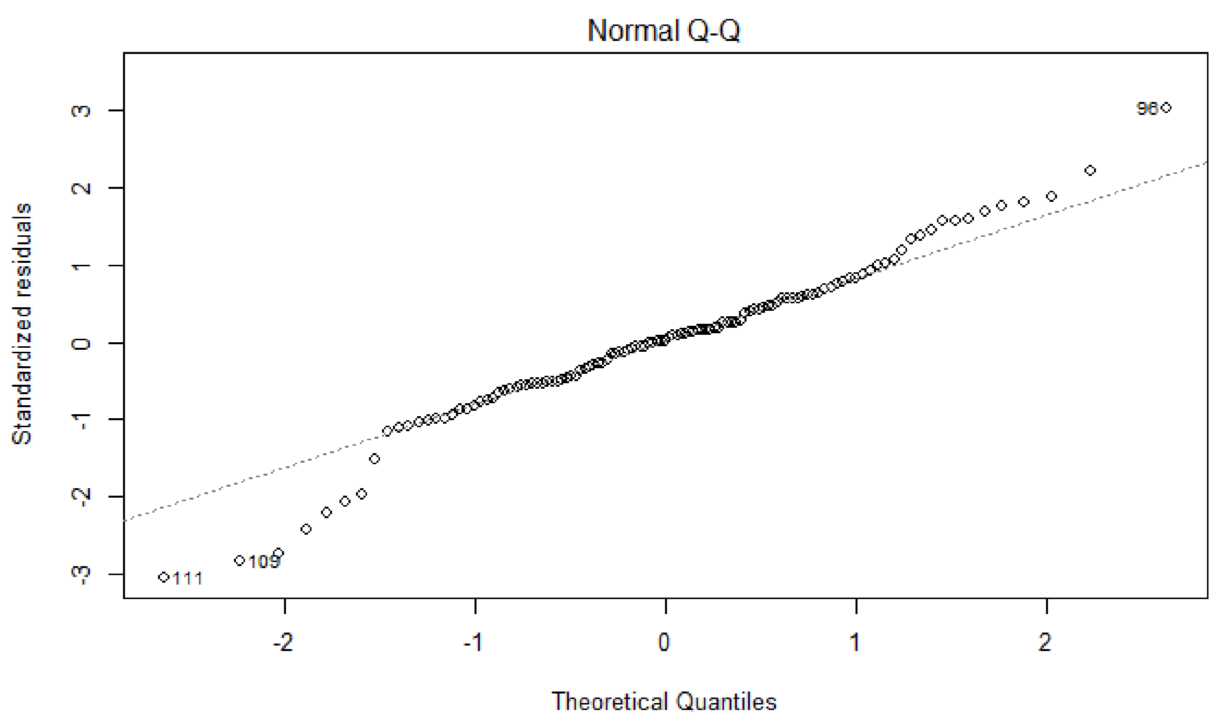


Residuals vs Fitted
Residuals
5e+05
0e+00
-5e+05
96
111
109
2000000
2500000
3000000
3500000
Fitted values

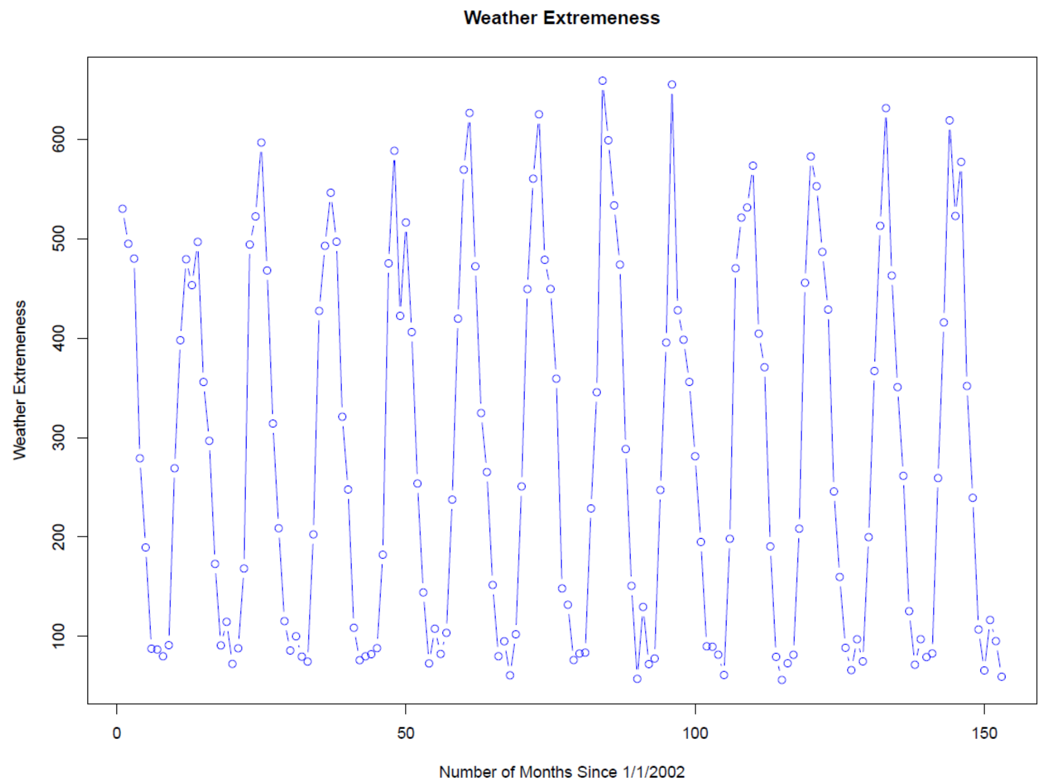


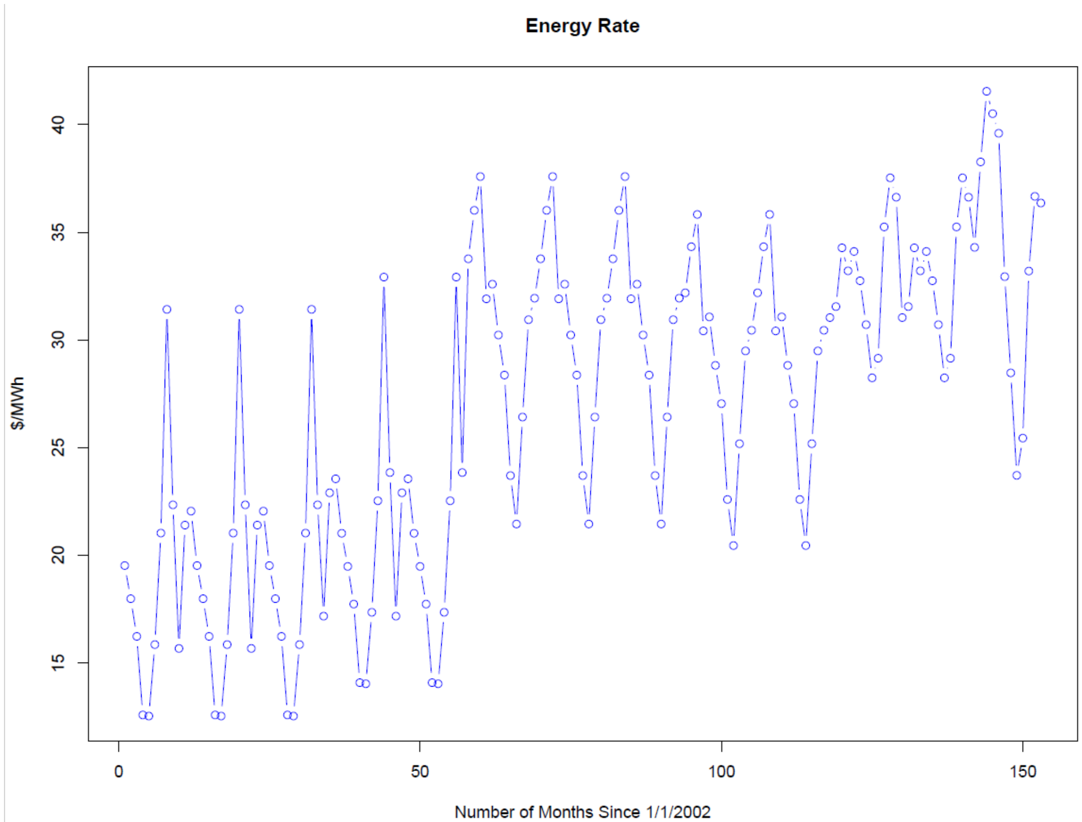
Histogram of sresid
Density
0.0
0.1
0.2
0.3
0.4
-4
-2
0
2
4
sresid

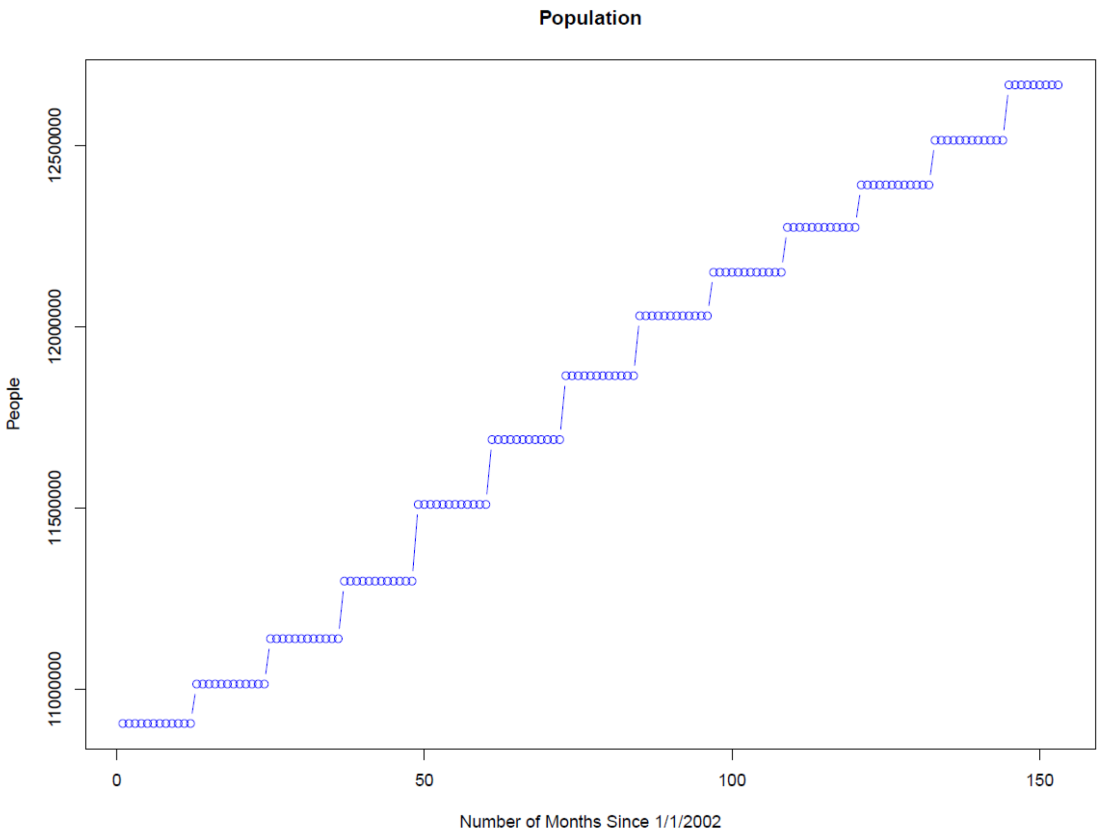

Residuals over Time
Residuals
6e+05
4e+05
2e+05
0e+00
-2e+05
-4e+05
-6e+05
0
20
40
60
80
100
120
Number of Months Since 1/1/2002

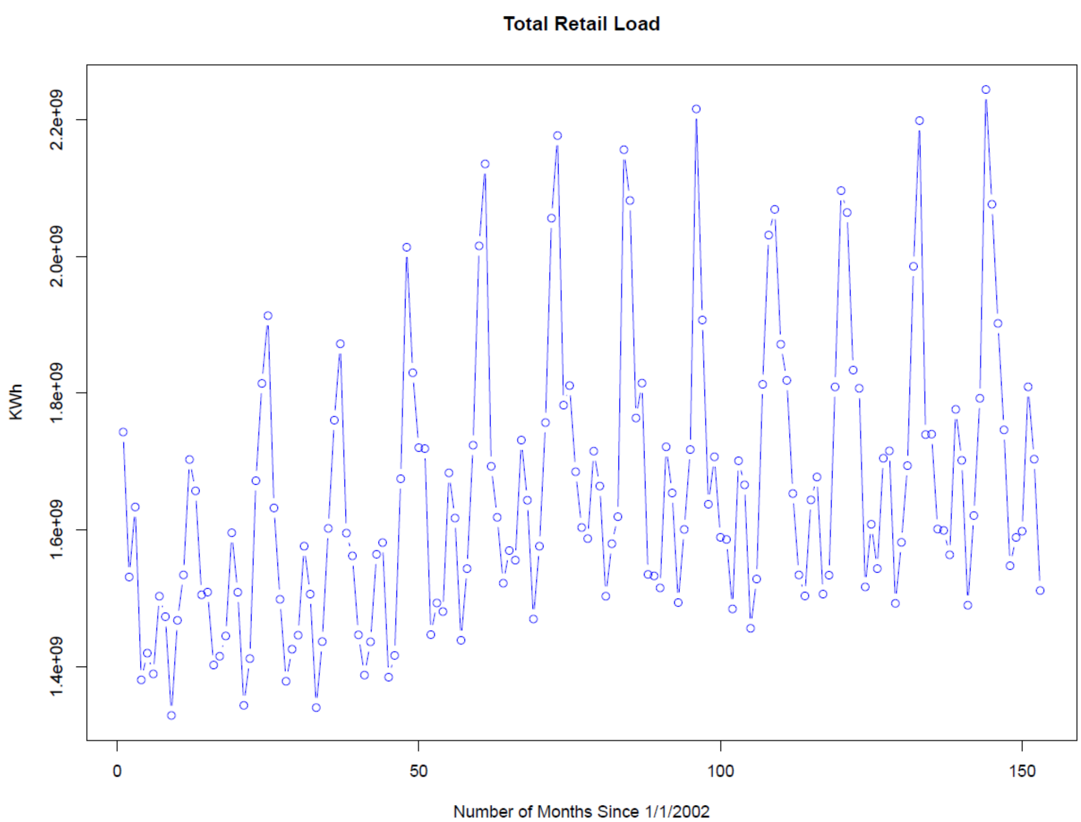

Normal Q-Q
Standardized residuals
3
2
1
0
-1
-2
-3
96
109
111
-2
-1
0
1
2
Theoretical Quantiles

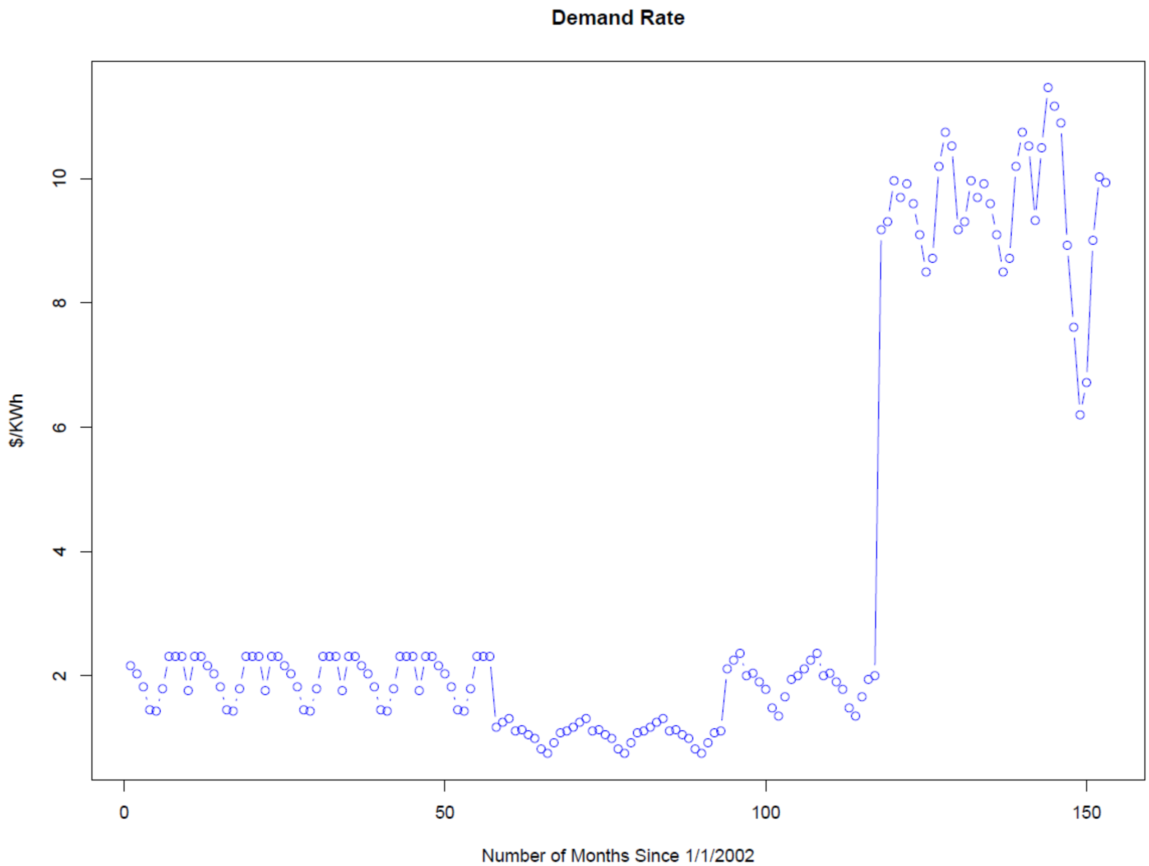
Appendix 6


Weather Extremeness
Weather Extremeness
100
200
300
400
500
600
0
50
100
150
Number of Months Since 1/1/2002


Energy Rate
$/MWh
15
20
25
30
35
40
0
50
100
150
Number of Months Since 1/1/2002


Population
People
11000000
11500000
12000000
12500000
0
50
100
150
Number of Months Since 1/1/2002


Total Retail Load
KWh
1.4e+09
1.6e+09
1.8e+09
2.0e+09
2.2e+09
0
50
100
150
Number of Months Since 1/1/2002


Demand Rate
$/KWh
Number of Months Since 1/1/2002
0
50
100
150
2
4
6
8
10

REFERENCES

Bonneville Power Administration. (2008). *Tiered Rates Methodology Rate Case: Direct Testimony.* Portland, OR: Bonneville Power Administration.

Bonneville Power Administration. (2012). Tiered Rate Methodology. In B. P. Administration, *Tiered Rate Methodology.* Portland: Bonneville Power Administration.

Faruqui, A. (2006). *The Economics of Dynamic Pricing and Smart Metering.* Dallas, Texas: The Brattle Group.

Faruqui, A., & Sergici, S. (2011). Dynamic pricing of electricity in the mid-Atlantic region. *Journal of Regulatory Economics*, 82-109.

Fenrick, S., & Getachew, L. (2007). *Demand Impact of a Critical Peak Pricing Program.* Madison, WI: Power System Engineering.

Rocky Moutain Institute. (2016). *A Review of Alternative Rate Designs.* Boulder, CO: Rocky Mountain Instititute.

Shy, O. (2008). *How to Price.* New York, NY: Cambridge University Press.

Taylor, T. N., & Schwarz, P. M. (1990). The long-run effects of a time-of-use demand charge. *RAND Journal of Economics: Vol. 21, No. 3,* 431-445.

Wolak, F. (2007). Residential Customer Response to Real-Time Pricing. *Center for the Study of Energy Markets*.

Wolak, F. (2010). An Experimental Comparison of Critical Peak and Hourly Pricing. *2010 POWER Conference.*